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Determinants of the variance of estimations on China's Carbon Emission: Based on Meta-Analysis

Qi Cui [a], Jun Yang [a], Wanlu Dong[a*]

[a] Center for Chinese Agricultural Policy, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Jia 11, Datun Road, Anwai, Beijing 100101, China

Abstract

China is confronting severe challenges to meet its rapidly increasing demand for energy and maintain its environments. It is well-known that China has become the world largest carbon emission country. However, there are huge different among different studies. As the accurate estimation of Carbon emission is critical and fundamental information for China's domestic policy and international negotiation. Based on the broaden and intensive literature reviews, the paper adopts a Meta-analysis method and the multi-factor variance analysis (ANOVA) to analyze the key factors that lead to the remarkable variations of estimations. Our results indicate the sources of researches and the choice of carbon emission coefficient affect the estimation significantly. The sources of researches, choice of carbon emission coefficient, energies classification and calculation based on national or provincial data are the four key determinants, accounting for 30.42%, 20.38%, 27.56% and 10.37% of variances of carbon emission estimations respectively. Interestingly, it is found that there is no significant difference among estimations based on industrial classification. According to our findings, it is proposed that the future studies to estimate China's carbon emission should pay extreme attentions on the detail classifications of energies and accuracy of carbon emission coefficient by different energies.

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Keywords: carbon emission; meta-analysis; carbon emission coefficient; energies classification; sources of researches

1. Research Background

* Corresponding author. Tel.: +86-010-64889019; fax: +86-010- 64856533.
E-mail address: dongwl.11s@igsnrr.ac.cn.

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China is confronting the great pressure of carbon reduction induced by its fast growth of economy at present and in the future, especially under the rising concerns of climate change globally. With the average annual real GDP growth rate of 9.9% in the last 3 decades, China has grown up as the second largest economy and first largest trade country in the world. Along with the rapid economic growth and dramatic change of economic, China's energy consumption rose significantly, increasing annually by 9.1% during 1992-2010, which was much faster than the world average of 2.6%. The economic growth pattern characterized by high-energy consumption dominated by coal contributes to China's rapid increase of CO2 emission. According to the statistic by Energy Information Administration (EIA), China has already overtaken the US, become the world's largest carbon emission country in by 2009, accounting for 23% of global CO2 emission. As the world largest developing country, the rapid economic growth in the future and huge carbon emission at present make China the focus of concern worldwide in term of the carbon reduction.

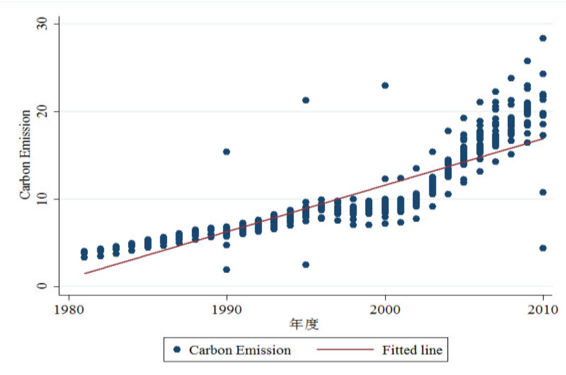

Fig.1 China carbon emission estimations (unit: 100 million tonnes)
Sources: authors' analysis

The huge variation of estimation on China's carbon emission leads to furious disputes on certain mitigate policies among academics and policy makers. Many studies have been carried out to estimate China's carbon emission domestically and globally. However, as shown in Fig.1, there is obvious divergence about the estimation. For example, according to the study of Hsiao et al. (2012), China's carbon emission is about 2.195 billion tons, which is more than one quarter of the estimation (1.723 billion tons) by Zhao et al. (2011). Moreover, the difference not only exists among academic researchers, but also among domestic authorities and international organizations. For example, the average carbon emission in 2007 is about 1.69 billion tons according to 3 domestic authorities[1], which is 0.14 billion tons less than the average (1.83) calculated based on 9 international organizations[2].

[1] 3 domestic authorities include Energy Research Institute (ERI) of China National Development and Reform Commission (NDRC), Development Research Centre of the State Council.

[2] 9 international organizations include Carbon Dioxide Information Analysis Centre(CDIAC), International Energy Agency (IEA), U.S. Energy Information Administration (EIA), Organization for Economic Co-operation and Development (OECD), World Resources Institute (WRI), Netherlands Environmental Assessment Agency (PBL), British Petroleum (BP), World Bank, The Institute of Energy Economics, Japan (IEEJ).

A lot of factors contribute to the huge variation among estimations, including methodology, data resources, industry classification, carbon emission coefficients etc. Taking carbon emission coefficients for example, the average estimations of China's carbon emission is about 1.72 billion tons in 2010 with adopting the carbon emission coefficient from Energy Research Institute (ERI) of China National Development and Reform Commission (NDRC). However, the average value would be 2.27 billion tones (about 31.7% higher) by using carbon emission coefficients published by Intergovernmental Panel on Climate Change (IPCC).

Therefore, it is very critical to analyze the reasons leading to the huge variation among different studies. The paper seeks to find out the key factors causing the huge variation of the estimation of carbon emission among studies. In order to realize the target, the comprehensive literature reviews are implemented to collect the related information from various quantitative studies on China's carbon emission. Based on the collected data, the comparison are made according to certain standards, and the Meta regression and multi-factor analysis of variances (ANOVA) are carried out to analyze the key factors and their contribution to the variation of estimation by studies. The paper is organized as follows: Section 2 introduces the methodology and data collection; Section 3 describes statistic results of various indexes; Sector 4 shows the results of Meta regression and ANOVA. The main conclusions are provided in the final part.

2. Meta analysis and Sample collection

2.1 Meta analysis introduction

Meta analysis is a kind of quantitative analysis instrument, which collects conclusions derived from multiple independent researches of the same kind to improve demonstration strength of research conclusions and valuation intensity of effect analysis. Furthermore, we can also combine multi-factor analysis of variances with Meta analysis to study factors causing difference among researches, and then hereby raise new questions for further research as reference. Meta analysis has been extensively applied in economic literature analysis area.

Meta analysis has several steps as follows: determine themes, design research programs and define literature inclusion and exclusion criterion; retrieve and collect existing literatures; classify and encode researches, then enter data; run Meta regression to make quantitative analysis for current research conclusions; apply multi-factors variance of analysis to decompose factors' relative contribution.

2.2 Sample and Data Collection

We use "carbon emission" and "dioxide carbon emission" in English and Chinese respectively as search terms to retrieve literatures in three databases: China National Knowledge Infrastructure (CNKI), Wanfang Data and ScienceDirect. To make sure homogeneity of literatures, we only collect the literatures, at least the themes or key words of which contain one of these search terms. To ascertain literatures' comprehensiveness, we also collect China carbon-emission estimation of international authorities, such as International Energy Agency (IEA), Carbon Dioxide Information Analysis Centre (CDIAC). Furthermore, we even incorporate domestic authorities' researches, for example 2050 China Energy and CO2 Emissions Report, Annual Review of Low-Carbon Development in China: 2010.

Our research laid particular emphasis on estimating China carbon emission occurred during the period from 2005 to 2010. According to the selection criterion mentioned-above, deleting researches that are qualitative analysis or duplicate published, we finally acquire 26 core-journals papers and 15 home-abroad authority reports to analyze by the end of August, 2013. These literatures all independently calculated China carbon emission; however, part of these researches just estimated CO2 emission, so we convert CO2 emission to carbon emission utilizing molecular weight relationship. Eventually all the emissions are measured by the unit “100 million carbon”.

We guess that some factors may contribute to the difference of research conclusions, these factors obviously including year variables, resources of research, choice of carbon emission coefficients, calculation based on national or provincial data, energy classification and industry classification. We control 2005-2010 years by year dummy variables, 6 years total. Resources of research can be classified into four categories: international authority, international scholar, domestic authority and domestic scholar. Therein the category international scholar refers to researches finished by foreign scholars as first author, or by Chinese scholars yet in overseas organizations. Carbon emission coefficients have three choices: ones published by IPCC; ones estimated by ERI; weighted average of various kinds of carbon emission coefficients. Energy classification has three categories: primary energy consumption, including coal, petrol and natural gas; primary energy consumption with cement production; primary energy with other energy consumption[1]. Calculation based on national or provincial data refers to whether papers calculate carbon emission for every province. Industry classification refers to whether papers calculate carbon emission for every industry.

We take each of annual carbon emission occurred during the period 2005-2010 in every literature as an observation. For example, paper 2 provided estimation of China carbon emission for 2005-2007, so this paper offered three observations. Then we classify and extend every observation to multiple independent samples in line with year variables, choice of carbon emission coefficients, energy resources, calculation based on national or provincial data and calculation based on industrial data or not. According to the method mentioned above, we finally classify 41 selected researches into 153 effective samples.

3. Descriptive statistical analysis of various indexes

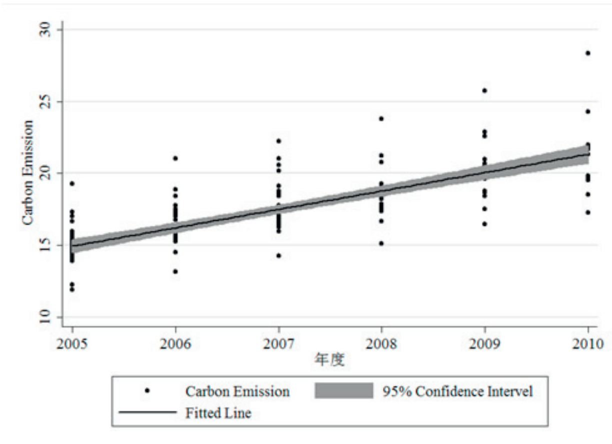

Fig.2 Carbon emission estimations in samples (unit: 100 million tons)
Sources: authors’ analysis

[1] Primary energy consumption includes coke, coal washing, diesel, gas and other processing products other than coal, petrol and natural gas. Other energy consumption refers to wind energy, hydropower, bioenergy and nuclear power energy.

Existing researchers found that carbon emission is increasing rapidly in China as Fig.2 showing. Existing researches' estimations of China carbon emission averaged at 1.49 billion tones for 2005, then fast rise to 1.78 billion tones for 2007, and further to 2.04 billion tones for 2010, annually growing 0.11 billion tones carbon. Fig.2 also shows that there is huge dispute for estimating China carbon emission among existing literatures, and that the dispute didn't narrow along with the time advancement.

There exists huge difference of China carbon-emission estimations among researches from various resources. Because we mainly focus on carbon emission occurred during the period 2005-2010, we choose carbon emission estimations for the year 2005 and 2007 which has most samples, and recent 2010 to comparatively analyze, the same pattern following. Table 1 outlines simple average of carbon emission estimations respectively derived from international authority researches, domestic authority researches, international scholar researches and domestic scholar researches. We found that estimations of international authority are obviously higher than those of domestic scholar and authority, and that the same situation also exits in international scholar, only except for 2007. Nevertheless, there is important difference between estimations of domestic authority and domestic scholar, and the same goes for international authority and international scholar. In general, foreign researchers' estimations of carbon emission are higher than Chinese researchers' whatever scholars or authorities. The estimating difference between home and abroad researches maybe directly influence climate negotiation results and confirmation of China carbon-reduction responsibility in climate negotiation procedures.

Table.1 Statistical analysis according to resources of researches (Unit: 100 million tons)

Resources of researches	2005		2007		2010	
	Mean	Obs.	Mean	Obs.	Mean	Obs.
International authority	15.55	9	18.26	9	22.59	6
International scholar	15.03	1	17.35	1	21.95	1
Domestic scholar	14.87	21	17.64	19	18.42	3
Domestic authority	14.43	4	16.90	3	21.34	1
Total	14.87	35	17.64	32	21.28	11

Sources: authors' analysis

Calculation based on national or provincial data has rather significant effect on research conclusions, as Table 2 showing. Most of existing literatures only calculate national carbon emission using nationwide data, instead of provincial carbon emission. We found that carbon-emission estimations based on provincial data are significantly more than that based on national data. Most literatures make use of statistical data with regard to energy consumption and high-emission industries to calculate carbon emission, in addition existing researchers also found that the summation of provincial energy-consumption data always exceeds the national summation. Accordingly, carbon-emission estimations based on provincial data are unsurprisingly more than those based on national data.

Table.2 Statistical analysis according to data resources (Unit: 100 million tons)

Data resources	2005		2007		2010	
	Mean	Obs.	Mean	Obs.	Mean	Obs.
Provincial data	16.23	5	18.58	3	0	0
National data	15.61	30	17.64	29	21.28	11

Source: authors' analysis

Choice of carbon emission coefficients also impacts carbon-emission estimations significantly. Table 3 shows that carbon emission estimations using IPCC emission coefficients are significantly more than those using ERI coefficients and estimations using weighted average of various coefficients lie somewhere in-between. This is because emission coefficients published by ERI only covers coal, petrol and natural gas; besides 3 primary energies, IPCC coefficients also cover coke, fine coal, coal gas, and diesel and so on. The weighted average of carbon-emission coefficients incorporate not only coefficients published by IPCC and ERI, but also coefficients published by Institute of Energy Economics in Japan (IEEJ), World Resources Institute (WRI) and so on.

Table.3 Statistical analysis according to carbon emission coefficients (Unit: 100 million tons)

Carbon emission coefficients	2005		2007		2010	
	Mean	Obs.	Mean	Obs.	Mean	Obs.
IPCC	14.91	23	17.67	18	22.71	9
Weighted average	14.88	7	17.66	7	19.50	1
ERI	14.48	6	17.79	7	17.24	1

Source: authors' analysis

Related to choice of carbon emission coefficients, energy classification has quite important effect on carbon emission estimations (Table.4). Carbon-emission estimations using primary energy and cement production data are obviously higher than those only using primary energy, and the same goes for estimations using primary energy and other energy. Though primary energy consumption still account for over 80% of carbon emission in China, however, due to cement production over 1.8 billion tones, carbon dioxide released in cement production procedure cannot be ignored at will. Other energies, such as hydroenergy, wind energy, nuclear power and bioenergy will also produce a small amount of CO_2 in both production and utilization procedures. These energies have been important sources of carbon emission along with their rapid development.

Table.4 Statistical analysis according to energy classification (Unit: 100 million tons)

Energy classification	2005		2007		2010	
	Mean	Obs.	Mean	Obs.	Mean	Obs.
Primary energy	14.87	23	17.70	19	22.04	8
Primary energy & Cement	15.97	4	17.99	3	24.27	1
Primary energy & Other energy	15.69	8	17.67	10	23.42	2

Source: authors' analysis

As Table 5 showing, carbon emission estimations based on industrial data are high than those based on national data, but not obviously. Our reviewed literatures and carbon-emission estimations will provide important reference to further industrial carbon-emission researches in the future.

Table.5 Statistical analysis according to industry classification (Unit: 100 million tons)

Data Classification	2005		2007		2010	
	Mean	Obs.	Mean	Obs.	Mean	Obs.
Industrial Data	15.69	8	17.68	7	22.04	4
National Data	14.90	27	17.64	25	20.75	7

Source: authors' analysis

4. Meta regression

4.1 Meta regression model

Meta regression is widely used in analyzing the impact on research conclusions of factors, such as research methods, model identification, data sources, and choice of parameters and so on. Meta regression mainly study variables' relationship through regression analysis, by taking key indexes of conclusion in existing literatures as the dependent variable and taking factors, like research method, data structure and model design and so on, as independent variables.

The basic model of Meta regression analysis is following:

$$Y_i = \beta_0 + \sum_{j=1}^{n} \beta_j * X_{ij} + \varepsilon_i \,, \quad i = 1,2, \ldots k$$

In the model above, the dependent variable Y_i is a statistical index of some research conclusion in the i^{th} literature, and independent variable X_{ij} stands for some controversial character in the same literature, such as the research method, features of data, model identification and so on. Coefficient β_j means marginal effects of the character j on research conclusion in existing literatures. ε_i is the error term in the Meta regression model. According to Nelson and Kennedy (2009), when incorporating kinds of literatures to Meta analysis, two possibilities must be considered: heterogeneity that can be handled by adding dummy variables; heteroskedasticity that can be alleviated by weighted OLS using the number of samples as weight. To get robust estimation, as Angrist and Pischke suggest (2009), we also report year-clustering standard error to account explicitly for heteroskedasticity due to carbon emission actually emitted in discrete years.

4.2 Meta regression results

We run Meta regression taking estimations of carbon emission occurred during the period 2005-2010 as dependent variables and 6 variables as independent variables, including resources of research, carbon emission coefficients, energy classification, calculation based on provincial or national data, industry classification and year dummy variables.

Details are following. Resources of research have 4 categories, so we choose international authority research as base group and add three dummy variables to the regression formula: international scholar (1=international scholar researches, 0=otherwise), domestic authority (1= domestic authority researches, 0=otherwise), domestic scholar (1= domestic scholar researches, 0= otherwise). Provincial data is a dummy variable (1=calculation based on provincial data, 0=calculation based on national data). Carbon emission coefficients have three choices, so we use IPCC coefficients as base group and add two dummy variables: ERI coefficients (1=coefficients published by ERI, 0=otherwise), Weighted average coefficients (1=weighted average of various coefficients, 0=otherwise). Energy classification can be sorted to three categories, so we choice primary energy as base group and add two dummy variables to regression: primary energy & cement (1=carbon emission from primary energy consumption and cement production, 0=otherwise), primary energy & other energy (1=carbon emission from primary energy and other energy consumption, 0=otherwise). Industry classification is other dummy variable (1=carbon emission calculated based on industrial data, 0=otherwise).

However, there exists heteroskedasticity in regression because the estimations we used come from different literatures in Meta regression; hence every literature has different number of observation samples to analyze. So it is necessary to utilize weighted ordinary least squared method in regression. In accordance with the method mentioned by Nelson and Kennedy (2009), we use the square root of the observation number incorporated to regression as weight. For example, literature 2 calculates China carbon emission for the period 2005-2007, so the number of observation samples used to analyze is 3; literature 3 only calculates carbon emission for 2005, namely only 1 observation sample. Obviously, the estimation results will be significantly influenced by the difference in the number of observation samples, which can be effectively handled by weighted OLS.

Be more subtle, there still existing a kind of heteroskedasticity weakening the power of our analysis, because carbon emission actually emitted in discrete years. It is possible that population variation of some year’s estimations correlate with other year’s, though which will not change our coefficient estimation, however, making the power of our analysis weak when doing causal inferring. Generally, as Angrist and Pischke suggest (2009), it is recommended to report clustering standard error in result, as we follow in this paper. The regression results are showing in Table 6 using weighted least squared estimation, and two columns report ordinary standard error and year-clustering standard error respectively. As we respected, two columns report the same coefficients, yet second column has more reasonable standard error. Finally, our conclusion does not differ significantly whether using ordinary standard error or clustering standard error.(1) Year dummies all have positive and significant coefficients consistent with our statistical analysis, showing that China carbon emission is increasing steadily along its trend. We can found that carbon emitted in 2006 is more than that emitted in 2005 on average, and then annual growth of carbon emission are 0.12, 0.09, 1.33 and 1.52 billion tons respectively from 2007 to 2010. China is experiencing rapid carbon-emission growth that annually exceeds 100 million tons, which reflects the growth style of high energy consumption and high emission in China nowadays. Rapid development of high emission sectors and products directly lead to high speed increase of carbon emission, which is estimated to rise from 1.49 billion tons in 2005 to 2.03 billion tons in 2010. On the other hand, China carbon emission has been always in the state of accelerating growth, except in the year 2008 when export decline and growth slowdown caused by global financial crisis temporarily dragged down carbon emission growth. Since 2008 carbon emission even increased more rapid than before, which to some extent results from China's economic simulating plan at that time that focus on industries of high energy consumption and high emission.

Table 6 shows regression results using weighted OLS, details as following:

VARIABLES	(1) Ordinary SE	(2) Cluster SE
2006	1.551***	1.551***
	(0.284)	(0.0157)
2007	2.782***	2.782***
	(0.297)	(0.0127)
2008	3.763***	3.763***
	(0.298)	(0.0154)
2009	5.094***	5.094***
	(0.408)	(0.0343)
2010	6.610***	6.610***
	(0.675)	(0.0570)
International Scholar	0.228	0.228
	(0.319)	(0.355)
Domestic scholar	-0.569	-0.569
	(0.378)	(0.283)
Domestic authority	-1.212***	-1.212***
	(0.411)	(0.0474)
Provincial data	2.717***	2.717***
	(0.475)	(0.246)
Weighted average coefficients	-0.738*	-0.738**
	(0.432)	(0.243)
ERI coefficients	-1.771***	-1.771***
	(0.401)	(0.254)
Primary energy & Cement	0.973***	0.973*
	(0.360)	(0.406)
Primary energy & other energy	2.241***	2.241***
	(0.393)	(0.365)
Industrial classification	0.534	0.534***
	(0.372)	(0.110)
Constant	14.67***	14.67***
	(0.236)	(0.128)
Observations	153	153
R-squared	0.779	0.779

Standard errors clustered by year in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: authors' analysis

(2) International scholar's coefficient is positive, but not significant. Meanwhile, domestic scholar's coefficient is positive and nearly significant. Domestic authority has negative and significant coefficient. Based on regression results, we make pairwise significance tests among all the four categories, and find that international scholar researches are significantly different from domestic scholar and domestic authority researches, but that domestic scholar researches is not different from domestic authority researches. Carbon emission estimations calculated by domestic scholar are 56.9 million tons less than estimations by international authority on average, with domestic authority 121 million tons less than international authority. Compared with international scholar, estimations calculated by domestic scholar are 79.7 million tons less, with domestic authority 144 million tons less. On the whole, foreign researchers calculated carbon emission estimations exceeding Chinese researches, which to some extent reflects the optimistic attitude with regard to carbon emission hold by Chinese researches. We believe that the different attitudes hold at home and abroad certainly have important impact on international climate negotiation and corresponding policy decision.

(3) Consistent with statistical analysis, calculation based on provincial data has positive and significant coefficient, meaning that estimations based on provincial data are 0.27 billion tones more than those based on national data, holding others constant. Existing literatures found that summation of provincial energy consumption generally exceeds national energy consumption, so unsurprisingly carbon emission estimations based on provincial data are larger.

(4) Weighted averaged coefficients and ERI coefficients are both significantly negative as we expect. As table 6showing, if using averaged emission coefficients, corresponding carbon emission estimations are 78.3 million tons less than those using IPCC coefficients. Furthermore estimations using ERI coefficients are 177 million tons less than those using IPCC coefficients. ERI coefficients only consider three kinds of primary energy-coal, petrol and natural gas, and even the emission coefficients of its items are less than IPCC coefficients. On the other hand, IPCC coefficients covered more kinds of high-emission energy, for example coal emission coefficient published by ERI is 0.7476 ton CO2 per ton standard coal; in contrast, IPCC further classify coal into raw coal, fine coal, coke and other coking products with their coefficients 0.7559, 0.7559, 0.855, 0.6449 ton CO2 per ton standard coal. Therefore, carbon emission estimations using IPCC coefficients are certainly more than those using ERI.

Weighted average emission coefficients just lie somewhere in between IPCC and ERI coefficients. In general, weighted averaged emission coefficients incorporate not only coefficients published by IPCC and ERI, but also kinds of coefficients from other authorities, such as IEEJ, WRI and so on. Therefore, weighted average coefficients are often something in-between IPCC and ERI coefficients; consequently, estimations using weighted average coefficients always lie in those using IPCC and ERI coefficients.

(5) Energy classification has significantly positive coefficient as respected. Table 6 showing that carbon emission estimations considering primary energy and cement production are 97.3 million tons more than those only considering primary energy. Carbon emission estimations will be even larger if considering other energy besides primary energy. Though primary energy accounts for over 80 percent of carbon emission in China, however, CO2 released in cement production approaches to 100 million tons due to huge cement output. Other energy, including bioenergy, wind energy, hydroenergy and power energy, also contributes over 200 million tons carbon to total carbon emission, especially as its share raises rapidly.

(6) Industry classification has positive and significant coefficient. It is the only case that conclusion based on clustering standard error largely differs from those on the basis of ordinary standard error. We can conclude that industry details should be considered when calculating carbon emission.

4.3 Multi-factor analysis of variance (ANOVA)

Based on Meta regression, we take advantage of multi-factor analysis of variance to further explore relative contributions of between-group variance in various variables to total variance in order to find main determinants finally leading to different conclusions. Table 7 is the ANOVA results, in which squared sum refers to squared sum of between-group variance among variables on the basis of their means. Hence we can get a contribution index of variables through dividing total squared sum by every variable's between-group squared sum. The significance test employed here is on the basis of F test, revealing whether between-group variance significantly influence total variance.

We make multi-factor analysis of variance with carbon emission estimations as dependent variables, and resources of researches, calculation based on provincial data, carbon emission coefficients, energy classification and industry classification as independent variables. As table 7 showing, we find that difference of carbon emission estimations in existing literatures can be mainly attributed to three factors: resources of researches, carbon emission coefficients and energy classification, which account for conclusion difference 30.42%, 20.38% and 27.56% respectively. They can explain 78.18% of our model in together and they are all significant at 95% confidence level. Though calculation based on provincial data is significant in Meta regression, it only can explain 10.37% of conclusion difference.

Table.7 Results of multi-factor analysis of variance (ANOVA)

Variables	Squared Sum	Freedom degree	Mean Square	F	Contribution Rate (%)
Model	299.11	10	29.91	5.31	100
Researches resources	91.01	3	30.34	5.38	30.42
Provincial data	31.014	1	31.01	5.50	10.37
Carbon emission coefficient	60.96	3	20.32	3.61	20.38
Energy classification	82.44	2	41.22	7.31	27.56
Industry classification	20.24	1	20.24	3.59	6.77
residual	805.88	143	5.64		
Total	1104.99	153	7.22		

Sources: authors' analysis

5. Conclusion

Actuarially estimating carbon emission has important reference value for China making carbon-reduction plans, dealing with international negotiation and adapting to climate change. Though the topics about carbon emission attract extensive attention from scholars and decision-makers, there is huge dispute on the theme how much carbon China emitted to the end. Therefore, existing research conclusions cannot provide powerful support for related policy decision.

We take advantage of and Meta analysis to review literatures relating to estimations of China carbon emission. Our Meta regression shows that there are five factors mainly causing difference of research conclusions: year dummy variables, resources of researches, calculation based on provincial data, carbon emission coefficients and energy classification. Furthermore, we find that resources of researches, carbon emission coefficients and energy classification are main determinants of research conclusion difference, and they account for conclusion difference 30.42%, 20.38% and 27.56% respectively. Though calculation based on provincial data is significant in Meta regression, it can only explain 10.37% of conclusion difference.

According to conclusion mentioned above, we should lay particular emphasis on carbon emission coefficients, energy classification and data characters in order to accurately calculate China carbon emission for future researches. We suggest that calculation method should be employed based on energy resources and carbon emission coefficients, using data in energy consumption and high-emission industries, selecting suitable carbon emission coefficients and paying attention to industrial and provincial difference. It is only on the basis of scientific calculating method that we can estimate China carbon emission precisely to provide effective reference for official decision-maker.

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